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Agricultural Land Markets – Efficiency and Regulation

Price dispersion in farmland markets: What is the role of asymmetric information?

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Abstract

This article investigates the role played by informational cost in agricultural land markets to explain price dispersion. Based on a hedonic model under incomplete information, we build a two-tier stochastic frontier. By linking costs of being information deficient to agent characteristics such as degree of professionalism, we identify relative price effects of buyers and sellers related to search. We compile a comprehensive data set of more than 10,000 transactions in Saxony-Anhalt, Germany, between 2014 and 2017. We find institutional sellers to achieve the lowest losses resulting from information deficiency while tenant buyers can benefit from informational advantages. We conclude that Germany's policy-makers can do more to support market transparency.

Key words: farmland markets, hedonic pricing, information deficiency, two-tier frontier

JEL classification: D82, D83, Q15, Q24

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Price dispersion has been traced back to heterogeneous buyer and seller groups in markets for homogeneous goods (cf. Kaplan et al. (2019) and cited literature therein). Farmland is a heterogeneous and unique good with a limited overall supply. Given its immobility, however, suitable substitutes are often lacking, most farmland markets are narrow with a high specificity of each transaction (cf. Borchers, Ifft, and Kuethe 2014), and even though capital may be mobile, market entry remains low despite increasing demand by investors. Trading volumes range between one and two percent in many regions of the Global North (Ciaian, Kancs, and Swinnen 2010; Bigelow, Borchers, and Hubbs 2016). Thus, farmland markets share characteristics of thin markets (Kuethe and Bigelow 2018).

Thin farmland markets present several problems. A seller's maximum willingness to pay may exceed a buyer's minimum willingness to accept. Expectations of surpluses over which they can bargain (Harding, Knight, and Sirmans 2003) may emerge. Search for the respective seller (buyer) with lowest (highest) willingness to accept (pay) is costly, as is finding substitutes. Gathering the information needed to establish an agricultural property's true market value may be expensive and time-consuming for the seller and buyer; depending on the respective search process and bargaining position, one or the other may influence the price (King and Sinden 1994). Hence, in addition to characteristics relevant for productivity[1], the information gathering proficiency and bargaining power of both seller and buyer matter (Polachek and Yoon 1987). Resulting agent-specific prices may neither send appropriate market information nor help in efficient price discovery.

Agent-specific prices have been traced to the different expectations held by new owners concerning a property's potential future returns (e.g., Brorsen, Doye, and Neal 2015). Price variations have also been explained by regional peculiarities, for instance, expectations of future land development in urban proximity (e.g., Plantinga and Miller 2001; Kolbe et al. 2015), zoning regulations in peri-urban markets (e.g., Eagle et al. 2014; Turner, Haughwout, and van der Klaaur 2014), the variety of agricultural policies (e.g., Graubner 2018),

[1]We refer to Nickerson and Zhang (2014) for an excellent overview on farmland price determinants.

the agglomeration effects of subsidized renewable energy production (e.g., Hennig and Latacz-Lohmann 2016; Towe and Tra 2013), and the local or regional market regulations (e.g., Lawley 2018).

The majority of farmland price studies have implicitly acknowledged remaining price variation by means of spatio-temporal effects (e.g., Maddison 2009), but that are hardly generalizable. Few studies have explored agent-specific prices due to thinness, such as price-sensitivity to farmer-buyer characteristics (e.g., Kuethe and Bigelow 2018) or price-effects due to the competition among potential farmer buyers (Margarian 2010). To our knowledge, only Cotteleer, Gardebroek, and Luijt (2008) have acknowledged agent-specific prices due to bargaining and market power. Typically framed within a hedonic pricing framework, these studies focus on average effects and do not consider the search process and the role of asymmetrically distributed information costs. One study has argued that such asymmetries produce different different bargaining positions with respective price-sensitivity (Curtiss et al. 2013). The results by these authors, however, lack external validity since estimation procedures have not been adjusted to acknowledge these asymmetries. Polachek and Yoon (1987) were the first to suggest a two-tier model which separates the observed prices into a hedonic part and three error components (noise, and seller- and buyer-specific price impacts) to account for the relative levels of agents' search and information costs. While studies of the real estate market have highlighted the role of asymmetric information in price schedules (Kumbhakar and Parmeter 2010), we have not found similar studies of farmland markets. Therefore, in this article we empirically investigate the role of the search process in farmland price formation.

We assume that the search process and respective additional cost can be related to a seller's degree of professionalism, for instance, a licensed real estate agent who often relies on auctions without bargaining, versus a private seller who primarily relies on negotiating, to understand the relative price relevance of the search process with potential losses for the less professional seller. On the buyer side, we link the categories of (non-)farmer and (non-tenant) farmer to asymmetries in the search process to identify the respective price effects of both parties. To differentiate seller- and buyer-specific effects, we construct a two-tier model of farmland prices within a hedonic price function with two additional one-sided error terms following Kumbhakar and Parmeter (2010). We specify the terms as functions of the observed characteristics of buyers and sellers using the scaling property (Parmeter 2018).

To validate the estimation approach, we compare our two-tier model based on the theory of thin markets to a reduced form of the model, where seller and buyer characteristics linearly add to the price function. We use a data set of more than 10,000 transactions for arable land from 2014 and 2017 in, Saxony-Anhalt, a heavily agricultural state in Germany. Its history of economic transition with a professional privatization agency makes the state an ideal setting for comparing different degrees of professionalism and searches on the seller side. We expect that modeling the hedonic price function within a stochastic frontier framework combined with spatial and temporal effects will help to mitigate the omitted variable biases that typically result from the data limitations in such models (Carriazo, Ready, and Shortle 2013). We find institutional sellers relying on public tenders to achieve the lowest losses resulting from information deficiency with markups. Farmer-tenant buyers benefit from informational advantages resulting in markdowns, with the exception of very small and very large transactions.

We believe that existing studies have largely underestimated the role of informational asymmetries by neglecting the explicit price-impact of buyers and sellers. Therefore, this article makes the following contributions. To our knowledge, it is the first to construct a two-tier model with a scaling property free of distributional assumptions about the error terms, and apply it to the agricultural sector.[2] Second, the model emphasizes the importance of making adjustments when analyzing prices in thin markets. Third, we hope it

[2]We refer to Bonanno et al. (2019) who applied a one-tier model to price the credence attributes of food

will inform the development of policy measures that support transparency and efficiency in farmland markets.

The remainder of the article is organized as follows. Section 2 explains the theoretical and econometric framework used. Section 3 describes the empirical strategy, the data, and the hypotheses. Section 4 applies the two-tier and simplified models to a comprehensive data set of agricultural transactions and discusses the results. Section 5 discusses the policy implications and gives suggestions for future research.

Theoretical model and estimation

A hedonic pricing model with incomplete information

We employ a search model with bargaining to identify the effects of asymmetric information on farmland prices. We assume that buyers and sellers enter the market with a set of beliefs about the distribution of prices, given the heterogeneity of the land. While agents may have different sets of information, they can invest in searches to improve their bargaining positions, for instance, by identifying competing offers from other sellers or buyers. We assume that all agents search optimally and that each buyer faces a trade-off between the search costs and finding a seller with a lower willingness to accept (WTA). Likewise, each seller faces a trade-off between the search costs and finding a buyer with the highest willingness to pay (WTP). Both search and informational costs may vary across agents, for instance, when local and non-local prospective buyers have different access to information, the cost variations are particularly relevant for substitutes. Similarly, an experienced professional seller may have lower search costs than a private seller with no experience. For instance, the professional seller may rely on tendering procedures that ease search finding the buyer with the highest WTP while the inexperienced private seller may rely on negotiations. In other words, when agents with higher search costs stop gathering information sooner, the buyers (sellers) with high search costs experience higher (lower) prices.

To model the search process under informational asymmetries, we use a hedonic pricing model following Kumbhakar and Parmeter (2010). We use the two-tier framework of Polachek and Yoon (1987) to incorporate information and search. Thus, the two additional one-sided error terms acknowledge the price impact of the buyer and seller characteristics related to search and informational cost.

According to the standard hedonic pricing model of Rosen (1974) under full information and thick markets, the hedonic price of farmland P_h is formulated as

$$(1) \quad P_h = h(x) + v,$$

where x denotes a vector of lot characteristics (e.g., lot size and soil quality), $h(.)$ is the hedonic price function, and v collects measurement errors and noise. In this model, price variation is only caused by heterogeneity and potential information asymmetries are disregarded.

To expand this model to our setting, we adopt a two-tier frontier model and apply it to buyers and sellers separately. The maximum WTP among buyers defines an upper bound of the market price, and the lowest WTA among sellers defines the lower bound. The price a seller receives, P_m^s, can be written as

$$(2) \quad P_m^s = P_b - u,$$

where P_b refers to the highest WTP by a potential buyer in the market and $u, u \geq 0$ denotes a seller's loss from information deficiency, that is, the loss caused by the inability to identify the buyer with the highest WTP. Likewise, the price a buyer pays, P_m^b, can be written as

$$(3) \quad P_m^b = P_s + w,$$

where P_s is the lowest WTA in the market, and $w, w \geq 0$ is the markup caused by being unable to identify the lowest WTA.

For a transaction to take place, the identical prices for buyer and seller form the market price P_m such that $P_m = P_m^b = P_m^s$. Using equations (2) and (3) yields $P_m = P_s + w = P_b - u$, which can further be rearranged such that

$$(4) \quad P_m + u - w = P_b - w = P_s + u,$$

where $P_s + u$ and $P_b - w$ are the hedonic prices for sellers and buyers, respectively, adjusted for their information. Since P_s, P_b, u, and w are unobserved, identification requires further assumptions. Kumbhakar and Parmeter (2010, p. 10) argue that $P_m + u - w$ corresponds to the price under full information given by the hedonic price P_h. Thus, using equations (4) and (1), the observed market prices can be expressed as

$$(5) \quad P_m = h(x) + v - u + w = h(x) + \varepsilon.$$

Equation (5) states that the observed market price of a lot consists of the implied characteristics of the lot $h(x)$, unobserved noise v, and the costs of information deficiency of sellers (u) and buyers (w). The composite error term ε collects noise and costs of information deficiency. Note that this model collapses to the standard hedonic pricing model if buyers and sellers have identical information deficiencies ($u = w$), including the case of fully informed agents ($u = w = 0$).

The current setting, however, assumes identical information deficiencies for all buyers and for all sellers. To allow for potential heterogeneity across agents, we follow Parmeter (2018) and model information deficiencies as functions of agents' characteristics. In particular, a buyer's information deficiency w is a function of buyer characteristics z_w, which may include knowledge of local market conditions. Likewise, a seller's cost of information deficiency is a function of seller characteristics z_u, which may include access to distribution channels. Extending equation (5) delivers the hedonic pricing model with incomplete information and buyer- and seller-specific costs of information deficiency, the regression equation can be formulated as

$$(6) \quad P_m = h(x) + v - u(z_u) + w(z_w) = h(x) + \varepsilon.$$

Estimation

To estimate equation (6), we employ the two-tier stochastic frontier model with scaling property proposed by Parmeter (2018). We define the respective costs of being information deficient in land transaction i $(i = 1, ..., N)$ as $u_i = u(z_{u,i}, \delta_u)$ and $w_i = w(z_{w,i}, \delta_w)$. The random variables u_i and w_i possess the scaling property if $u_i = u(z_{u,i}, \delta_u) = g_u(z_{u,i}, \delta_u)u_i^*$ and $w_i = w(z_{w,i}, \delta_w) = g_w(z_{w,i}, \delta_w)w_i^*$, where $g_u(.) \geq 0$, $g_w(.) \geq 0$, and both u_i^* and w_i^* are independent from z. The functions $g_u(.)$ and $g_w(.)$ are termed scaling functions, and the distributions of u_i^* and w_i^* are the basic distributions (cf. Wang and Schmidt 2002).

Imposing the scaling property implies that u_i and z_i follow common distributions given by u^* and w^*, respectively, which are weighted by observation-specific scales $g_u(z_{u,i}, \delta_u)$ and $g_w(z_{w,i}, \delta_w)$. Therefore, characteristics z_u and z_w affect the scale of the functions $u(z_{u,i}, \delta_u)$ and $w(z_{w,i}, \delta_w)$, respectively, but not their shape. Thus, u^* and w^* define the baseline costs of information deficiency. The actual cost of information deficiency, however, depend on buyer and seller characteristics via the scaling functions $g_u(.)$ and $g_w(.)$.

To impose the scaling property in our econometric model, we specify the means of the basic distributions as $\mu_u^* = E[u_i^*]$ and $\mu_w^* = E[w_i^*]$ (Alvarez et al. 2006). Further, to account for the non-negativity restrictions from the theoretical model regarding u and w, we use exponential functions such that $g_u(z_{u,i}, \delta_u) = e^{z'_{u,i}\delta_u}$ and $g_w(z_{w,i}, \delta_w) = e^{z'_{w,i}\delta_w}$. Given the imposed non-linearity of the deficiency terms, the resulting model can be estimated with non-linear least squares (NLS) by solving

$$(7) \quad (\hat{\beta}, \hat{\delta_u}, \hat{\delta_w}, \hat{\mu_u^*}, \hat{\mu_w^*}) = \min_{(\beta, \delta_u, \delta_w, \mu_u^*, \mu_w^*)} \frac{1}{n} \sum_{i=1}^{N} \left[y_i - h(x_i, \beta) + \mu_u^* e^{z'_{u,i}\delta_u} - \mu_w^* e^{z'_{w,i}\delta_w} \right]^2.$$

The minimization delivers the parameters of interest: coefficients β that represent the implicit values of lot characteristics x, the scale parameters of the costs of information deficiency μ_u^* and μ_w^*, and the impact of buyer and seller characteristics z_u and z_w captured by δ_u and δ_w. Identification of δ_u and δ_w requires $\mu_w^* e^{z'_{w,i}\delta_w}$ to be different from $\mu_u^* e^{z'_{u,i}\delta_u}$. Valid inference for the parameter estimates needs to account for heteroscedasticity in the composite error term; thus, procedures for robust standard errors within NLS frameworks have to be used (Parmeter 2018). Further, an equivalent model specification can include the scale parameters into the exponential functions as intercepts to be estimated.

Applying an estimation procedure based on the scaling property has several advantages. First, although further assumptions on $w(z_w)$ and $u(z_u)$ are required, no distributional assumptions for the terms are necessary, which allows estimation with NLS. On the contrary, efficient estimation with Maximum Likelihood would require correct distributional assumptions for both inefficiency terms. Second, while standard tools can be used for estimation of NLS, there is no closed form solution for the likelihood function of a two-tier stochastic frontier. Third, contrary to retrieving u and w by deconvolution of a composite error term based on unobservables as proposed by Kumbhakar and Parmeter (2009, 2010), the scaling property allows recovering estimates of u and w directly from observables z_w and z_u.

In order to validate our results, we contrast the non-linear two-tier model estimated by NLS to a linear model estimated by ordinary least squares (OLS), where the scaling variables linearly enter the hedonic part of the model. Except for the intercept, OLS parameter estimates for the hedonic function are unbiased and consistent if the error components are uncorrelated with the hedonic characteristics, and can thus serve as a benchmark (Parmeter 2018).

Empirical strategy

Our aim is to analyze the role played by informational asymmetries between different buyer and seller groups in farmland price formation and empirically investigate this question for the eastern German land market. We begin by describing the farm structure and land market in eastern Germany and why we use Saxony-Anhalt's transaction sales data between 2014 and 2017 to validate our two-tier model. This is followed by the hypotheses and the empirical model.

Background

The agricultural structure and the farmland market in eastern Germany, where Saxony-Anhalt is located, have been influenced by expropriation, land collectivization, and socialist policies. Historically, many large farms were located in Saxony-Anhalt due to the highly fertile farmland. As they have been primarily subject to expropriation after 1945, the share of land to be privatized after the German reunification in 1990 was high compared to other eastern German states. Since its foundation as a successor to the German privatization agency (*Treuhandanstalt*) in 1992, BVVG (*Bodenverwertungs- und - Verwaltungs GmbH*) privatizes formerly state-owned agricultural and forest land in eastern Germany on behalf of the Federal Ministry of Finance. Originally, BVVG leased out land under long-term contracts, but since 2007 it uses public tenders according to German privatization principles and in line with European law.

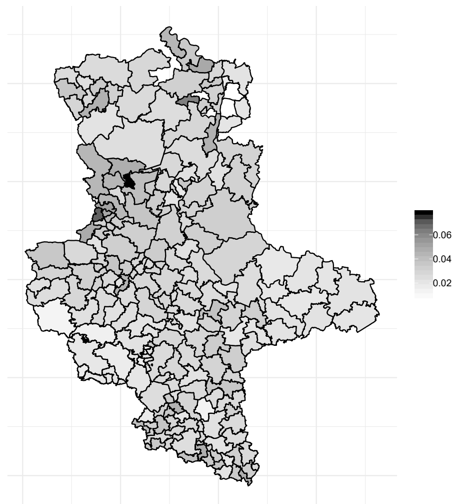
Today, the formerly state-owned farms and typical socialistic production cooperatives operate as cooperatives or corporations, but also single farms have newly or re-established the business. By 2016, where most recent numbers are available, in eastern (western) Germany more than 70 (90) percent of farms operate as single farms (BMEL 2018a) and comprise about 29 percent of the total utilized agricultural area (StaLa 2017). The share of land operated by legal entities and cooperatives is nearly 50 percent in eastern Germany, while less than 1 percent in western Germany (BMEL 2018a). In 2016, farms in eastern Germany were about 223 hectares on average and operated at 67.5 percent rental land (BMEL 2018b). In the same year, farms in Saxony-Anhalt were 270 hectares on average, which is the second highest regional average in Germany, and operated at a high land lease share of around 72 percent (StaLa 2017). Since 2010, contrary to western Germany, rental shares have been decreasing since 2010 in eastern Germany (BMEL 2018a).

Against this backdrop, the farmland market of Saxony-Anhalt developed dynamically: Between 2007 and 2017, mean prices more than tripled from 5,055 €/ha to 17,903 €/ha. However, while Saxony-Anhalt had the second highest average prices of Germany's eastern states, the German average was still higher with about 24,064 €/ha (Destatis 2018). To illustrate price dispersion in the land market, we take 2017, the most recent year in our data set: there were 3,172 farmland transactions of approximately 8,400 hectares in total; less than one percent of the total agricultural area was transacted with an average plot size of about 2.68 hectares. The trading volume already varies across Saxony-Anhalt (cf. right part of figure 1): local transactions range from less than 10 transactions for half of the municipalities to more than 50 in five municipalities. The median prices per soil quality index point[3] as shown in the left part of figure 1 reveal considerable variation across the state but without obvious spatial patterns. Against this backdrop, the need for a quantitative assessment of seller and buyer-specific prices to explain this price dispersion seems obvious.

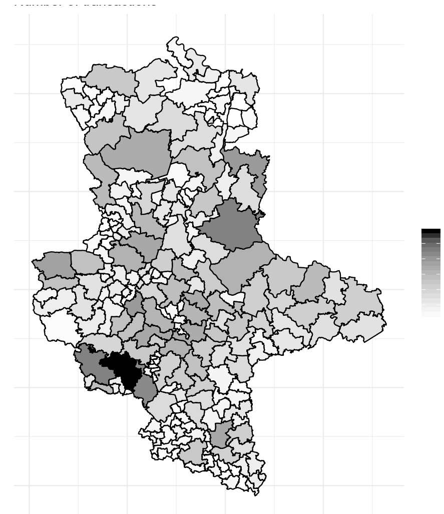
Data

Our data set consists of 12,134 land market transactions for arable land in Saxony-Anhalt between 2014 and 2017 taken from the Committee of Land Valuation Experts (*Gutachterausschuss für Grundstückswerte in Sachsen-Anhalt*, LVermGeo 2018a). Transaction details include contract date and price, lot characteristics (location, size, and soil quality), and anonymous buyer and seller information. We select only arm's-length transactions and remove observations with missing or inconsistent values. Additional outlier detection based

[3]Soil quality index is an official index for Germany to unify pedologic, scientific, and (agro-) economic considerations including water availability within one measure for arable land ('Ackerzahl') and grassland ('Grünlandzahl'). Low (high) numbers indicate low (high) productivity (German Bundestag 2007). For Saxony-Anhalt, values for arable land range between 20 and 104.



(a) Median price €/m² per soil quality index point



(b) Number of land transactions

Figure 1. Saxony-Anhalt farmland market 2017 at municipal level

on the minimum covariance determinant estimator (Rousseeuw and van Driessen 1999) results in a data set of 10,778 observations.

To better understand price variation for the same fundamental value and to separate seller and buyer-specific effects, we consider lot characteristics in the hedonic function, and variables explaining the environment in which the transaction occurs. Since many studies have shown the price impact of subsidized renewable energy sources on land market prices (e.g., Haan and Simmler 2018; Towe and Tra 2013), we use information from the State Office for Survey and Geoinformation (LVermGeo 2018c), the State Office of Statistics (StaLa 2018) and the Federal Network Agency (BNetzA 2018), and add the density of wind power and biomass capacity in a municipality, measured as the number of turbines and the electric capacity per ha of agricultural land, respectively. We indicate if a lot is in a wind energy area, which allows building a wind turbine, to capture high potential future earnings from this alternative land use.

Likewise, we consider BVVG's local share of the total number of transactions in the respective municipality in the price analysis. To calculate BVVG's local share, we consider all transactions in the year of a respective transaction and the preceding two years in a given municipality. Such a contribution to transparency may decrease informational costs in regions with many BVVG transactions for all participants.

As shown in table 1, the mean price over all transactions is about 1.63 €/m^2, but varies between less than 0.30 €/m^2 and more than 4 €/m^2. The transacted lots have an average size of about 3 ha, but the distribution ranges from less than 0.03 ha to more than 100 ha. 86 % of the lots can be operated independently (e.g., no further right of way is necessary), and 1 % of the transactions lie in a region eligible for wind energy use. 66 % of the transacted lots are leased out.

Also as shown in table 1, on the seller side, BVVG as the major player carries out about 8 % (910 observations) of all transactions in the data set. Public and professional sellers each carry out about 2 % (256 and 181 observations). BVVG and professional sellers sell on average larger lots, where professional sellers additionally sell at higher soil quality and more often allow for independent operation. Public sellers sell at lower soil quality and lots are less often leased out (for brevity, see Appendix, table 5). On the buyer side, farmers buy 74 % (8,006 observations). Former tenants are the buyers in 49 % (5,264 observations) and farmer as former tenants are the buyers in almost 50 % (5,236 observations). Lot heterogeneity is less pronounced when differentiating on the buyer side with only minor differences (cf. table 5).

Hypotheses

Germany's post-communist economic transition changed the composition of land ownership from state to a mix of private, restituted owners, and new and former owners that have been buying land in the privatization process. Given this mix, figuring out price formation remains challenging. Therefore, we develop the following three hypotheses.

Hypothesis 1: Seller information deficiency

Table 1. Descriptive statistics for data set, 2014–2017

N = 10,778		Mean	Median	SD	Q1	Q99
Dependent variable						
Price (€/m^2)	P	1.63	1.50	0.86	0.35	4.08
Lot Characteristics						
Lot size (ha)	x_S	3.08	1.02	6.40	0.03	26.93
Soil quality (Index)	x_Q	64.11	66.00	22.65	21.00	100.00
Lot independence (1/0)	x_I	0.86	1	0.35	0	1
Lot is leased (1/0)	x_L	0.66	1	0.47	0	1
Wind energy area (1/0)	x_W	0.01	0	0.08	0	1
Controls at municipal level						
Wind power turbines per ha	m_W	0.002	0.001	0.003	0	0.02
Biomass capacity kW per ha	m_B	0.33	0.1	2.44	0	2.58
Transaction share of BVVG	m_{BVVG}	0.12	0.09	0.10	0.00	0.48
Seller Characteristics						
BVVG (1/0)	$sBVVG$	0.08	0	0.28	0	1
Professional seller (1/0)	$sProf$	0.02	0	0.13	0	1
Public seller (1/0)	$sPub$	0.02	0	0.15	0	1
Buyer Characteristics						
Farmer (1/0)	bF	0.74	1	0.44	0	1
Tenant (1/0)	bT	0.49	0	0.50	0	1
Farmer and tenant (1/0)	bFT	0.49	0	0.49	0	1
Farmer and non-tenant (1/0)	$bFNT$	0.26	0	0.44	0	1

Note: Due to data privacy reasons, we cannot report minima and maxima.

We hypothesize that information deficiencies for private sellers will be higher than for professional sellers, but higher for professional sellers than for BVVG.

BVVG as the major player in Saxony Anhalt's farmland market has around 20 % market share by acreage on average, and up to 60 % in some regions (LVermGeo 2018a). BVVG relies on tendering procedures, where auction rules, bidding requirements, and auction results are publicly available on the BVVG website and published in local media and farmers' magazines. BVVG's professionalism and level of specialization is hypothesized to ease the search process and finding potential buyers with the highest WTP. Potential buyers may further perceive lower risks concerning a transaction failure when considering BVVG. This may even attract potential buyers and further ease search. Therefore, BVVG may benefit, and fostered by the auction mechanism we hypothesize higher prices compared to other sellers. That is, this group is expected to incur lower losses of information deficiency than other sellers.

Although private owners continued to transact on their own, others began to use licensed real estate agents. These professional sellers use, for example, procedures comparable to public tenders, and advertise and target potential buyers efficiently. Due to this professionalism, we expect lower costs of information deficiency for these sellers compared to private sellers without experience. However, compared to BVVG, real estate agents have a lower turnover rate and thus we expect the markup to be lower for this group. As a third group, public authorities such as municipalities or local governments may benefit from experience but at a lower extent compared to real estate agents. This advantage may further be off-set by costs caused by a potential principal agent problem: public sellers' goal may not primarily be selling at profit maximizing prices, and lower prices might be accepted due to time limitations and missing incentives to invest in search (cf. Attkinson and Halvorsen 1986).

Hypothesis 2: Buyer information deficiency

We hypothesize that informational deficiencies for farmers and tenant buyers will be lower than for non-farmers, but higher for non-tenant farmers than for tenant farmers.

On the buyer side, we can distinguish by farmers and non-farmer buyers, and whether the buyer was the former tenant. Thus, we cannot clearly rank by professionalism, we can rather rely on asymmetric knowledge: farmers and tenants in particular are hypothesized to be better informed about potential returns from land-use and the local land market conditions. This informational advantage may in particular be relevant for expected alternative supply offers at the time of the bidding. This may result in lower costs for information acquisition for these groups and might offer to form more realistic expectations about the returns reducing the likelihood of overpaying (e.g., winners' curse). In our second hypothesis, we expect a price decreasing effect of tenancy: as a result of the existing relation between sellers and tenants prior to the transaction, social capital on both sides might influence the price by reducing search cost (e.g., Kostov 2010; Robinson, Myers, and Siles 2002). This social capital may result in a reduction of cost of being information deficient for tenant farmers compared to non-tenant farmers and non-farmers.

Hypothesis 3: Information advantage based on lot size

We hypothesize that farmers and/or tenants have a price advantage over non-farmers and/or non-tenants that is increasing in plot size.

Identification of a pure farmer effect may be challenging (cf. Croonenbroeck, Odening, and Hüttel 2019), in particular since both groups, farmers and non-farmers, are rather heterogeneous. Both groups could contain investors and it may rather be the intention on how to use the land after purchase that determines willingness to invest in search (e.g., Magnan and Sunley 2017). This is why we consider that informational advantages of tenants and potentially farmers with the intention to use that land could vary in plot size. For instance, for larger plots, the group of non-farmer buyers may be less heterogeneous since these lots do not reasonably allow alternative land use apart from farm operation such as horse keeping, gardening or real estate (Brorsen, Doye, and Neal 2015). We further expect larger transactions to be less heterogeneous in terms of lot constitution and valuation.[4] Since val-

[4]We refer to Yiu, Wong, and Chau (2009) for evidence in real estate market

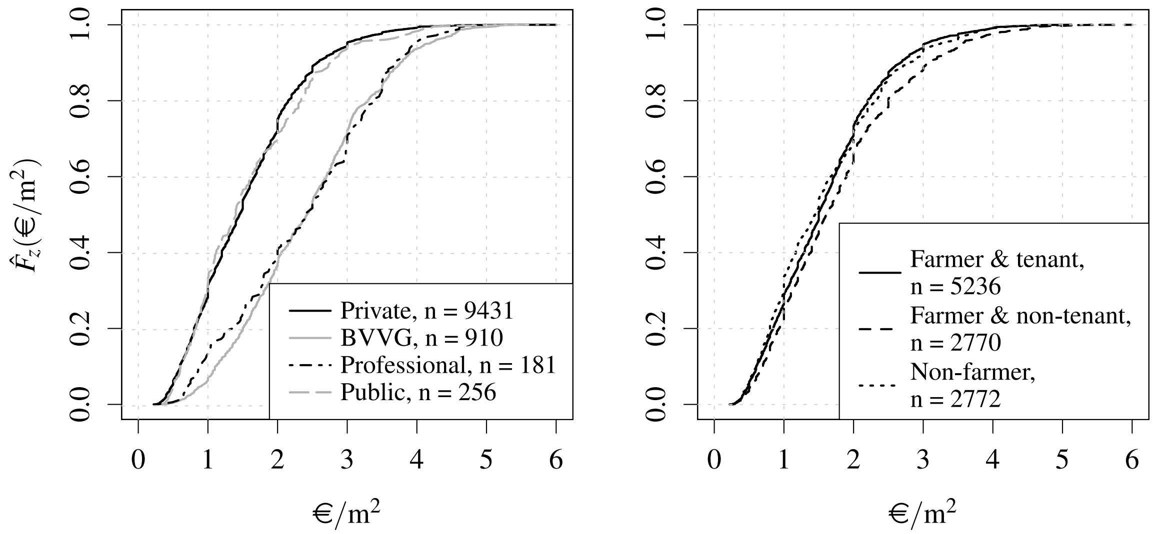


Figure 2. Unconditional cumulative density functions of prices paid by seller type (left) and buyer type (right)

uation is mainly based on the conventional and observable determinants of farmland prices, this allows tenants and farmers to better use their knowledge about the expected returns. Therefore, under hypothesis 3 we suspect larger plots to be sold with price markdowns to farmers and/or tenants that increase with lot size.

Descriptive evidence: seller and buyer specific price differentials

We use the data set to systematically investigate the unconditional cumulative distribution function of the raw prices by buyer and seller type. As shown in figure 2, there are differences in prices between professional, public and private sellers in the raw data. There are, however, only small differences between the three potential combinations of (non-)farmers and (non-)tenants types in the raw data, with the exception of slightly higher prices for non-tenant farmers.

Model specification

To test the three hypotheses, we use log-linear regression equations consisting of a hedonic part $h(x)$ and the combined error term ε that collects noise and the information deficiency costs for buyers and sellers. Based on a Box-Cox transformation for the continuous variables, lot size and soil quality, we enter them into the model in power transformations and in interaction, and enter other regional continuous variables such as renewable energy sources linearly. To capture the implicit spatio-temporal effects, we use twelve location indicators LC_k based on regional classes provided by the Committee of Land Valuation Experts (LVermGeo 2018b).[5] We model the time effects by using linear-quadratic trend, τ and τ^2, as well as a locally differing trends by interacting the trend variables with the location indicators. The regression equation can be formulated as

$$
\begin{aligned}
log(P) = {} & \beta_S \sqrt{x_S} + \beta_Q \sqrt{x_Q} + \beta_{SQ}(x_S \cdot x_Q) + \beta_I x_I + \beta_L x_L + \beta_W x_W \\
& + \gamma_W m_W + \gamma_B m_B + \gamma_{BVVG} m_{BVVG} + \gamma_\tau \tau + \gamma_{\tau^2} \tau^2 \\
& + \sum_{k=1}^{12} \gamma_{LC,k} LC_k + \sum_{k=1}^{12} \gamma_{LC,\tau,k} (LC_k \cdot \tau) + \varepsilon,
\end{aligned} \tag{8}
$$

where the β's denote the respective hedonic parameters to be estimated and γ's denote the parameters for regional variables at the municipal level and the time- and spatial effects.

We consider two models, $TT1$ and $TT2$ using the two-tier approach with differing error term specifications ε by model (cf. table 2). Both models obey an identical specification of the seller side: dummy variables for BVVG, other professional, and public sellers (hypothesis 1). On the buyer side, in $TT1$ we assess whether information asymmetries for tenant and non-tenant farmers compared to non-farmers exist and if they are price influencing (hypothesis 2). We also assess whether the informational advantages are more pronounced depending on the size of the transaction (hypothesis 3).

To test these hypotheses, indicators of tenant and non-tenant farmers enter the error term interacted with lot size.[6] To test hypothesis 3 we enhance model $TT1$ by adding interaction terms of lot size and its square with buyer characteristics. This gives model $TT2$ that allows us to test whether buyer-specific price effects are sensitive to lot size. As shown in table 2, δ denote the parameters to be estimated and capture the impact of buyer and seller

[5] Each location class represents a geographically compact area with similar characteristics, such as connection to infrastructure. Refer to figure 7 in the Appendix for a map.

[6] A simpler model specification failed to converge probably caused by the high overlap of the two buyer indicators and missing variation over transactions.

Table 2. Specifications of the error term ε

Model	$\varepsilon = -u(z_{u,i}, \delta_u) + \omega(z_{\omega,i}, \delta_\omega) + v$
LIN	$\alpha + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf$ $+\delta_{bFT,x_S}(bFT \cdot x_S) + \delta_{bFNT,x_S}(bFNT \cdot x_S) + v$
$TT1$	$-exp[\mu_S + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf]$ $+exp[\mu_B + \delta_{bFT,x_S}(bFT \cdot x_S) + \delta_{bFNT,x_S}(bFNT \cdot x_S)] + v$
$TT2$	$-exp[\mu_S + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf]$ $+exp[\mu_B + \delta_{bFT,x_S}(bFT \cdot x_S) + \delta_{bFNT,x_S}(bFNT \cdot x_S)$ $+ \delta_{bFT,x_S^2}(bFT \cdot x_S^2) + \delta_{bFNT,x_S^2}(bFNT \cdot x_S^2)] + v$

characteristics, where μ_B and μ_S denote the baseline cost of information deficiency for buyers and sellers (μ_w^* and μ_u^*). We estimate them as intercepts of the exponential functions to ensure that the sign of the effect of the costs of being information deficient on the price is consistent with theory. The baseline cost of information deficiency is required to scale the impact of the respective buyer and seller characteristics, but will not be interpreted directly. Finally, we compare the findings of the two-tier model and a linear benchmark model LIN, where the seller and buyer characteristics linearly add to the hedonic part. Model LIN includes an intercept α, which is omitted in the two-tier model, to identify baseline inefficiency terms μ_B and μ_S, respectively. Both models share an additional noise term v.

We estimate models $TT1$ and $TT2$ using the NLS procedure and estimate the linear benchmark model LIN using OLS. To account for heteroscedasticity induced by the composed error term, we refer to multiway clustered standard errors with clusters corresponding to combinations of thirty quantiles of lot size and the squared soil quality.[7]

[7] All calculations are performed with R (R Core Team 2019). NLS estimation uses the nls function from the stats package. Estimation of robust standard errors uses the sandwich package (Zeileis 2004). To ensure convergence, we run estimations for the non-linear models 5000 times with random starting values. R codes are available upon request.

Results

Table 3 lists the models' parameter estimates for the hedonic variables and the buyer and seller characteristics; see table 6 in the appendix for the estimates of spatial controls and time trends. Overall, the models show satisfactory goodness of fit as indicated by the squared correlation coefficient of about 0.67 across all models. The hedonic estimates are strikingly similar across the different specifications. As noted by Kumbhakar and Parmeter (2010), the intercept of *LIN* corresponds to the sum of the baseline cost of being information deficient if $E[w-u]=0$, otherwise OLS-estimates would be biased. A comparison with the sum of the baseline terms in $TT1$ ($-2.142 \approx -e^{0.925}+e^{-0.990}$) does not indicate such bias. In this case, the estimates of the benchmark model *LIN* represent average effects for sellers and buyers.

In line with previous studies, we find positive coefficients of soil quality and lot size (e.g., Lehn and Bahrs 2018), although non-linear (e.g., Maddison 2000; Sheng, Jackson, and Lawson 2018). Including the negative interaction coefficients, the price effect of additional size decreases in size, whereas the price effect for higher quality soils may be too costly, that is, the effect of additional size can even reverse (cf. figure 3 for $TT1$). In the latter case, capital or borrowing constraints may also increase (Brorsen, Doye, and Neal 2015). Interestingly, we note that whether a lot can be independently used and leased out is irrelevant for the price vector. Other studies, however, have indicated a potential relationship between the price effect of lot size and an independent use (e.g., Gluszak and Zygmunt 2018).

A recent study by Haan and Simmler (2018) using aggregated data found significant land-owner effects in other regions of Germany, whereas we find that regional renewable energy production does not influence the price of individual farmlands. Other studies using transaction data, however, found significant effects of biomass based energy production on rental prices in boom years (e.g., Hennig and Latacz-Lohmann 2016).

Table 3. Parameter estimates for hedonic variables and buyer and seller characteristics

N = 10,778	*LIN*		*TT*1		*TT*2	
Lot characteristics						
Intercept	−2.142***	(0.053)				
$\sqrt{\text{Size}}$	0.125***	(0.010)	0.134***	(0.010)	0.107***	(0.010)
$\sqrt{\text{Quality}}$	0.202***	(0.005)	0.203***	(0.006)	0.200***	(0.005)
Quality · Size	−0.0001***	(0.00002)	−0.0001***	(0.00002)	−0.00003	(0.00003)
Independence	−0.001	(0.011)	−0.004	(0.011)	−0.001	(0.011)
Wind energy area	−0.007	(0.048)	−0.006	(0.047)	−0.001	(0.046)
Lot is leased out	−0.015*	(0.009)	−0.014	(0.009)	−0.012	(0.008)
Regional characteristics						
Wind power turbines	−0.435	(0.964)	−0.431	(0.965)	−0.321	(0.958)
Biomass capacity	0.002	(0.001)	0.002	(0.001)	0.002	(0.001)
BVVG share	0.155***	(0.055)	0.150***	(0.054)	0.149***	(0.054)
Seller characteristics						
Baseline cost			0.925***	(0.055)	0.905***	(0.058)
BVVG	0.390***	(0.016)	−0.167***	(0.009)	−0.169***	(0.011)
Public seller	0.070*	(0.037)	−0.028*	(0.015)	−0.028*	(0.015)
Professional seller	0.185***	(0.024)	−0.077***	(0.012)	−0.075***	(0.011)
Buyer characteristics						
Baseline cost			−0.990***	(0.381)	−1.055**	(0.441)
Farmer · tenant · size	−0.006***	(0.002)	−0.027**	(0.011)	−0.008***	(0.001)
Farmer · non-tenant · size	−0.0001	(0.001)	−0.001	(0.003)	0.040**	(0.016)
Farmer · tenant · size^2					−0.001***	(0.0002)
Farmer · non-tenant · size^2					−0.002***	(0.0005)

Note: Clustered standard errors (at thirty quantiles of lot size and the squared soil quality) in parentheses.
Asterisks indicate the following: * = $p<0.1$; ** = $p<0.05$; *** = $p<0.01$.
Parameter estimates for location classes, time dummies and interactions are reported the Appendix.

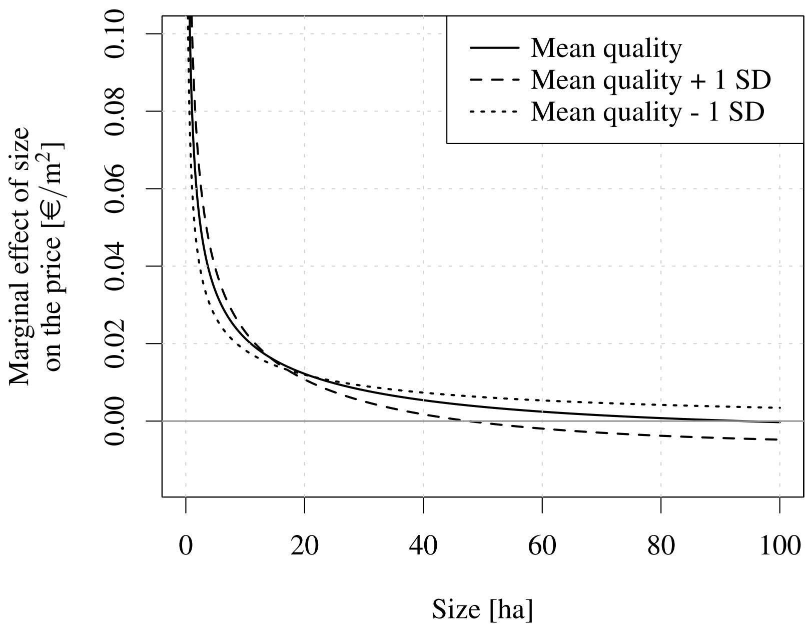


Figure 3. Marginal effect of lot size on the price for different soil qualities based on $TT1$

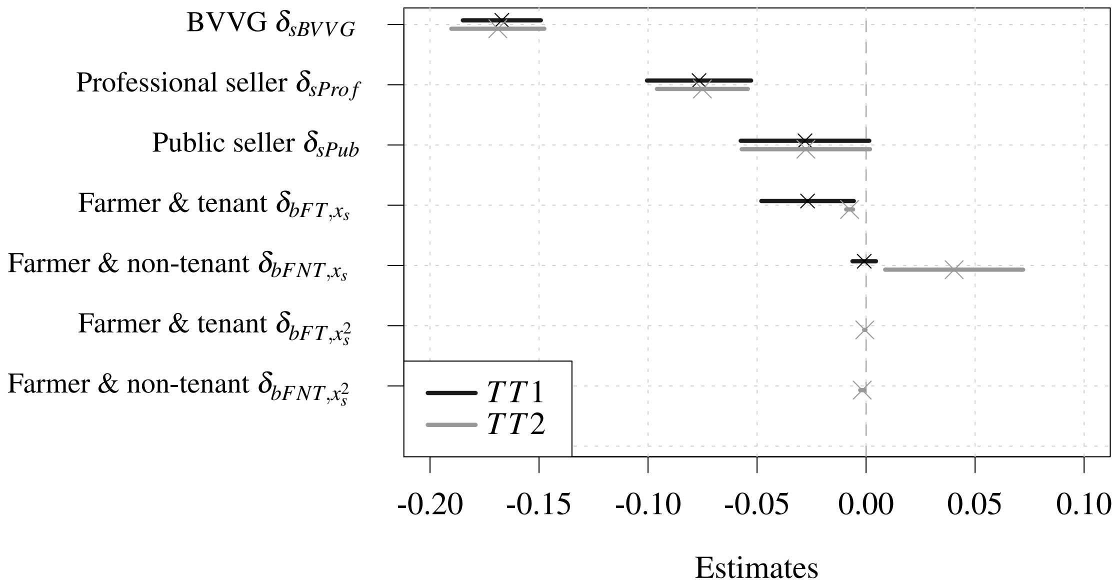


Figure 4. Parameter estimates and 95 % confidence intervals for buyer and seller variables

Results underline relevance of BVVG's regional activities: a 1 % increase in the share of transactions corresponds to a 0.15 % price increase, a finding which is contrary to Hüttel, Wildermann, and Croonenbroeck (2016). In regions and times when BVVG has a higher share, overall market transparency may be higher. This is because BVVG's tendering procedures offer more information on the market volume and their policy to publish transaction data may ease forming a bid. As a result, prices could be closer to the competitive price. BVVG's dominance over space and time, however, may also be evidence of market power.

Figure 4 summarizes the estimates of seller and buyer variables for models $TT1$ and $TT2$. Respective positive δ coefficients indicate increasing information deficiency with the respective variable, and negative signs indicate the opposite. Regarding price effects, a positive δ parameter for one buyer type indicates a higher price for this group compared to the reference (non-farmer, non-tenant). A positive parameter on the seller side, however, indicates lower prices for the respective seller group compared to the reference group (non-professional sellers).

Models $TT1$ and $TT2$, which both show statistically significant negative parameter estimates for the three seller types, reveal that professional seller groups obtain higher prices

Table 4. Marginal effects of seller and buyer types evaluated at the sample mean

	$TT1$			$TT2$		
	€/m^2	%	$p-value$	€/m^2	%	$p-value$
Seller						
BVVG	0.70	47.41	0.000***	0.68	46.82	0.000***
Professional	0.30	20.44	0.000***	0.29	19.57	0.000***
Public	0.11	7.22	0.000***	0.10	6.97	0.000***
Buyer						
Farmer	0.00	−0.10	0.942	0.06	4.04	0.000***
Tenancy	−0.04	−2.81	0.000***	−0.08	−4.82	0.000***
Tenant farmer	−0.04	−2.90	0.099*	−0.02	−0.98	0.214

Note: Asterisks correspond to: *p<0.1; **p<0.05; ***p<0.01.
P-values based on standard errors retrieved using the delta method.

(hypothesis 1). This finding may be related to the benefits, that is, lower cost of being information deficient. The two models and the simplified model indicate the strongest effect for BVVG, followed by professional sellers and public sellers. The order of these effects suggests that information deficiency decreases with professionalism and level of specialization, for instance, professional sellers invest more in targeting potential buyers and in advertising which reduces search cost. To quantify these markups, table 4 lists the marginal effects of the seller types evaluated at the sample mean. BVVG's markup of 0.70 €/m^2, corresponds to 47 % higher prices, whereas professional sellers' obtain 20 % higher prices compared to private sellers, and public vendors obtain 0.11 €/m^2 higher prices. While BVVG's price effect may reflect a high level of professionalism, the markup may also relate to the use of first-price auctions with public tenders. Auctions deliver higher revenues than negotiated sales (e.g., Bulow and Klemperer 1996), where empirical evidence for the real estate context exists (e.g., Chow, Hafalir, and Yavas 2015).

To illustrate the non-linear relation of the seller-specific price-effects, figure 5 shows the price differences of BVVG (left panel), professional sellers (middle) and public sellers (right panel) compared to private sellers depending on lot size and soil quality, using model $TT1$ and holding other variables fixed at their respective sample means. We note that the

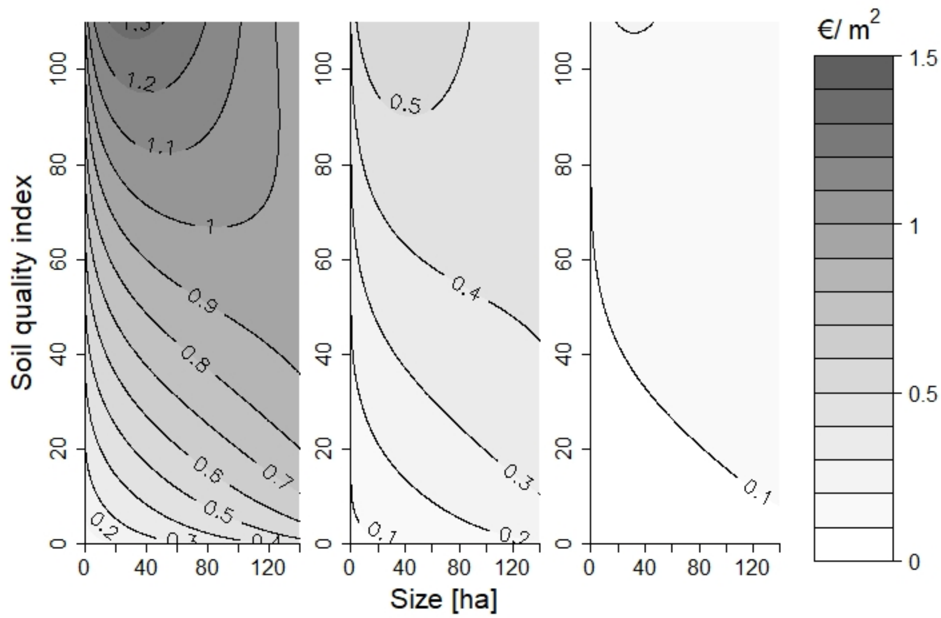


Figure 5. Differences in predicted prices for BVVG (left), professional sellers (middle) and public sellers (right) compared to private sellers based on $TT1$

gap between prices for private sellers and all seller types is small for lots with low quality, and higher for medium sized lots with very high quality. Competition for high quality soil lots may be higher for medium sized lots, given the valuation of soil quality. Search cost may be more relevant for larger sizes also for professional sellers, where the financial constraints of buyers may come into play. BVVG's price markups show strongest increases with lot size and quality among all sellers. Again, BVVG's professionalism may be a factor, but strategic supply management may be another. We note that few observations in our sample are both, large and of high quality and hence predictions may suffer from extrapolation bias.

Regarding the buyer side, both models $TT1$ and $TT2$ indicate price effects for farmer buyers being tenants (cf. lower part of figure 4). The magnitude of the parameter estimates varies across the models, but the marginal effect of tenancy, calculated as the difference of predicted prices between a tenant and a non-tenant farmer, differs only slightly: in $TT1$ the tenancy effect is -0.04 €/m^2 and in $TT2$, it is around -0.08 €/m^2. The tenant farmer effect compares the predicted prices for a farmer buyer being a tenant to a non-agricultural buyer: using mean lot characteristics (3.08 ha, 64.11 soil quality points), the tenant farmer effect corresponds to 2.90 % (0.98 %) lower prices, respectively, if the tenant buys. The negative price impact may indicate a lower cost of informational deficiency for this group compared to non-farmers, because farmers being tenants may have better knowledge of substitutes (hypothesis 2). The models, however, show non-robust effects for farmers not being tenants. Contrary to $TT1$, $TT2$ shows that non-tenant farmers pay 0.06 €/m^2 more than non-farmers for an average plot, or about 4 % higher prices (cf. table 4).

We infer that the heterogeneity of the farmer and non-farmer groups may account for the rather small positive effect at the mean. For the non-tenant farmer group, we speculate that the identified effect may even be diluted since we would expect different effects whether a non-tenant is local or not. This information, however, was unavailable in the data set, but we did suspect that the group of buyers may be more heterogeneous for smaller lots, because of a larger usage portfolio, such as gardening, horse-keeping, or speculation on infrastructure or housing, particularly in urban proximity. Significant interaction terms of buyer identity with lot size indicate the relevance of size in support of our hypothesis. The terms suggest that information deficiency-effects on the buyer side are non-linear in lot size. To illustrate these effects, figure 6 shows, for $TT1$ (left panel) and $TT2$ (right), the predicted prices for different buyer types as a function of the lot size with other variables fixed at the sample mean.

For both models, the plots show a price difference between tenant farmers and other buyer types that increases in transaction volume, but in model $TT2$, which includes a linear-quadratic size term (cf. right panel of figure 6) the tenant effect decreases after approximately 20 ha, and the plots larger than 40 ha show no price effect (hypothesis 3). We attribute the fact that tenant farmers appear to pay less for medium-sized lots to lower search and information costs, because tenants are probably familiar with local market conditions, particularly alternatives, which may be relevant for medium-sized lots. While there is no

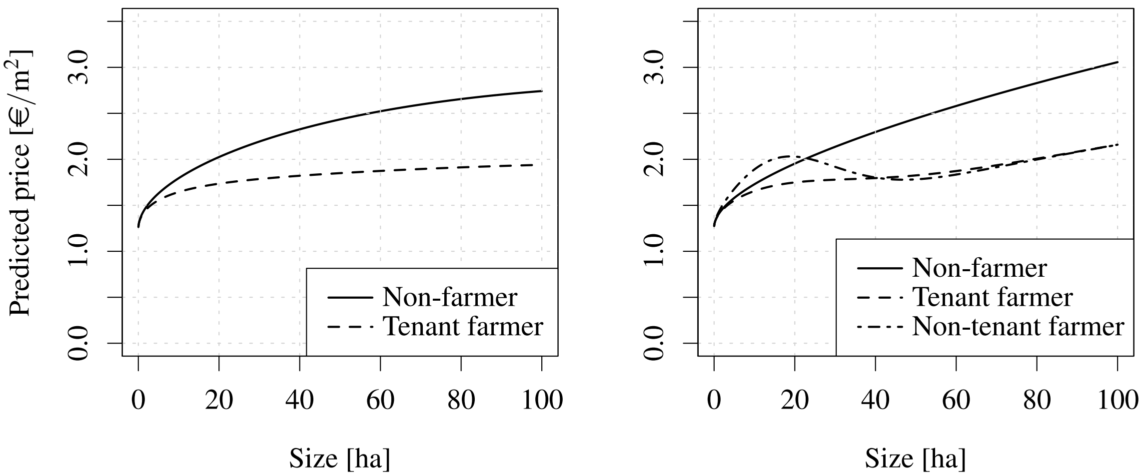


Figure 6. Predicted prices by buyer type for model $TT1$ (left) and $TT2$ (right)

price difference between farmers due to tenancy for very large plots, farmers still achieve a markdown compared to non-farmers; a result that could not be obtained from the simpler size-relation in $TT1$. Likely, farmers are able to use their informational advantage regarding the sector and potentially benefit from experiences compared to non-farmers for larger lots, where local tenants act as other farmers do, as investors. However, the effects for very large plots may suffer from out-of-sample predictions and should be interpreted with care.

Concluding remarks

Within this article we investigate the role of asymmetric information and search cost in the price formation in thin farmland markets. We analyze how the asymmetries related to buyer and seller characteristics can explain price dispersion for the same fundamental value. We build a two-tier stochastic frontier model with a scaling property free of distributional assumptions regarding the error terms, basing it on a hedonic model under incomplete information and relating the search costs to the degree of professionalism on the seller side and the informational advantages of (non-)farmers and (non-)tenants on the buyer side. We formulate three hypotheses and empirically assess them using a data set of more than

10,000 transactions between 2014 and 2017 in the agricultural state of Saxony-Anhalt in Germany.

The results affirm the important role played by information asymmetries and the search process in the thin farmland market. While controlling for conventional hedonic characteristics, such as lot size and soil quality, determines land prices, we find that buyer and seller characteristics explain price dispersion for the same fundamental value. For the seller side, our results support our hypothesis that professionalism and experience decrease information and search costs. We find that information deficiency decreases with professionalism and level of specialization, and that BVVG, the largest seller, obtains the lowest losses, followed by professional private sellers, public, and private sellers. We conclude that targeted strategies, marketing campaigns, and skillful use of the media give professional sellers a significant informational advantage and reduce the cost of searching for buyers with the highest willingness to pay.

On the buyer side, we find that farmers and tenant farmers use sector knowledge and information about local market conditions to obtain lower price and search costs. Former tenant farmers appear to have a significant informational advantage, particularly for substitutes in the near term. We also propose two explanations for our finding of a relationship between tenants' alleged informational advantages and medium-sized lots. First, smaller lots may comprise additional heterogeneity, for instance, potential rezoning or alternative land use. Second, the group of non-tenants may compromise farmer and non-farmer investors and thus larger lots may comprise a less heterogeneous group of buyers.

From an academic perspective, our results imply that explicitly modeling informational asymmetries will allow the cost of incomplete information to be identified. If information asymmetries are correlated with hedonic characteristics, not acknowledging implications of these asymmetries in the modeling approach is likely to lead to inefficient estimation and biased coefficients for the hedonic function. From a policy perspective, our results imply that increasing market transparency will lead to more efficient markets. In particular, our results emphasize the weak position of private sellers who have difficulties searching for information about farmland transactions because of cost, outdated or missing data, etc. While BVVG currently remains the major source of market data, we suggest that it will no longer be the case after re-privatization is completed in 2030. To support a more level playing field on the supply side, policies aiming at market efficiency should ease access to information.

Based on the research in this article, we suggest several directions for future research. First, a simple binary coding of farmers/non-farmers and tenants/non-tenants may not cover all relevant dimensions of the information asymmetries, therefore resulting in a heterogeneous counterfactual. Further, such differentiation may hinder identification because of a strong overlap among the groups. To overcome these issues, we suggest a more detailed recording of buyer characteristics with potential intentions to use the land. Second, the role of market power as it affects both supply and demand merits investigation when a large player dominates local and regional markets or maintains an informational advantage. The interplay between land sales and rental markets should be explored in more detail. We also suggest that a deeper understanding of the roles played by speculation effects and bargaining power in thin markets will be beneficial for policy-makers.

Appendix

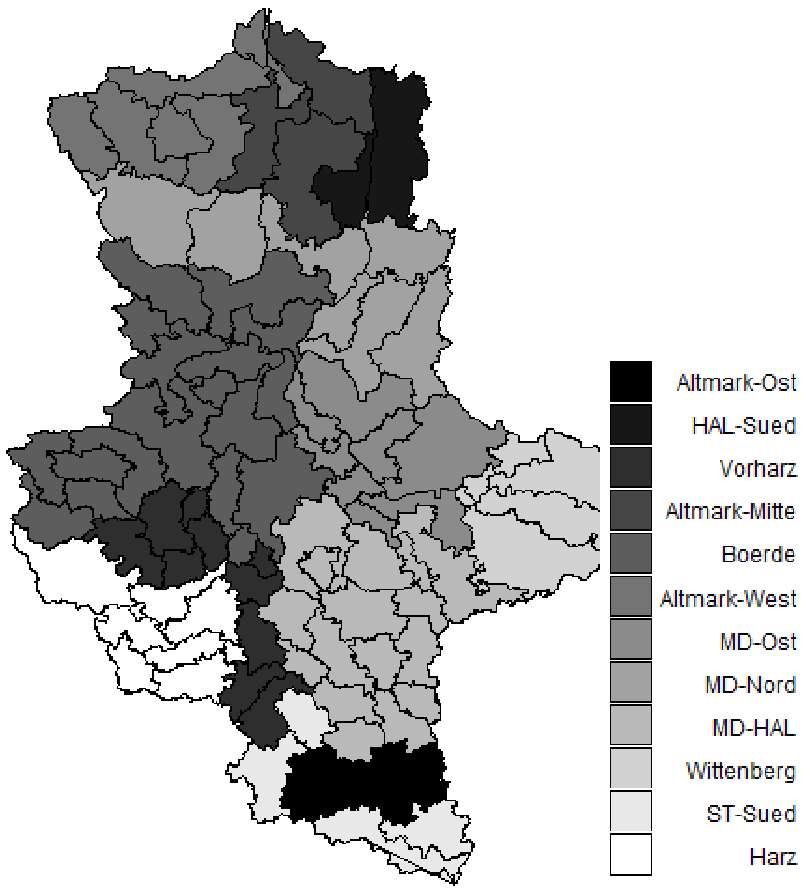


Figure 7. Map of location classes

Table 5. Descriptive statistics by seller and buyer types

	Mean	Median	St. Dev.	Q1	Q99
Seller: BVVG					
Price (€/m^2)	2.43	2.42	1.00	0.60	4.77
Lot Size (ha)	8.17	3.38	14.73	0.03	90.66
Soil Quality (Index)	63.91	65.00	21.99	21.00	99.00
Lot Independence (1/0)	0.86	1.00	0.35	0.00	1.00
Wind energy area (1/0)	0.00	0.00	0.07	0.00	0.00
Lot is leased (1/0)	0.67	1.00	0.47	0.00	1.00
Seller: Professional Seller					
Price (€/m^2)	2.37	2.42	1.06	0.57	4.61
Lot Size (ha)	5.65	4.58	7.61	0.06	23.00
Soil Quality (Index)	70.71	75.00	22.29	22.00	99.00
Lot Independence (1/0)	0.94	1.00	0.23	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.07	0.00	0.00
Lot is leased (1/0)	0.69	1.00	0.46	0.00	1.00
Seller: Public Seller					
Price (€/m^2)	1.58	1.40	0.89	0.41	4.13
Lot Size (ha)	4.39	0.82	10.94	0.02	68.37
Soil Quality (Index)	59.18	58.50	23.13	20.10	100.00
Lot Independence (1/0)	0.72	1.00	0.45	0.00	1.00
Wind energy area (1/0)	0.00	0.00	0.00	0.00	0.00
Lot is leased (1/0)	0.48	0.00	0.50	0.00	1.00
Buyer: Farmer					
Price (€/m^2)	1.65	1.52	0.86	0.35	4.18
Lot Size (ha)	3.36	1.18	6.68	0.06	29.06
Soil Quality (Index)	64.93	67.00	22.42	21.00	100.00
Lot Independence (1/0)	0.89	1.00	0.31	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.09	0.00	0.00
Lot is leased (1/0)	0.78	1.00	0.41	0.00	1.00
Buyer: Tenant					
Price (€/m^2)	1.59	1.50	0.81	0.35	3.96
Lot Size (ha)	3.02	1.00	6.43	0.06	28.21
Soil Quality (Index)	65.50	68.00	22.32	21.00	100.00
Lot Independence (1/0)	0.89	1.00	0.31	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.09	0.00	0.00
Lot is leased (1/0)	0.88	1.00	0.33	0.00	1.00

Note: Due to data privacy reasons, we cannot report minima and maxima.

Table 6. Regional and time control variable estimates

N = 10,778	*LIN*		*TT1*		*TT2*	
Location classes						
Altmark-Mitte	0.347***	(0.077)	0.345***	(0.077)	0.346***	(0.077)
Altmark-Ost	0.098	(0.092)	0.098	(0.092)	0.095	(0.092)
Altmark-West	0.273***	(0.070)	0.273***	(0.071)	0.278***	(0.071)
Boerde	0.673***	(0.045)	0.672***	(0.046)	0.673***	(0.046)
HAL-Sued	0.474***	(0.045)	0.474***	(0.045)	0.470***	(0.045)
Harz	0.078**	(0.039)	0.077**	(0.039)	0.077**	(0.039)
MD-HAL	0.515***	(0.033)	0.516***	(0.034)	0.516***	(0.034)
MD-Nord	0.180***	(0.039)	0.179***	(0.039)	0.183***	(0.038)
MD-Ost	0.462***	(0.049)	0.460***	(0.049)	0.460***	(0.049)
ST-Sued	0.563***	(0.045)	0.561***	(0.045)	0.555***	(0.046)
Vorharz	0.428***	(0.046)	0.427***	(0.046)	0.427***	(0.045)
Time trend						
Trend	0.161***	(0.020)	0.160***	(0.020)	0.161***	(0.020)
Trend^2	−0.012***	(0.003)	−0.012***	(0.003)	−0.012***	(0.003)
Interactions						
Altmark-Mitte · trend	0.009	(0.023)	0.008	(0.023)	0.009	(0.023)
Altmark-Ost · trend	0.038	(0.030)	0.037	(0.030)	0.04	(0.030)
Altmark-West · trend	0.013	(0.025)	0.012	(0.026)	0.012	(0.025)
Boerde · trend	−0.021**	(0.009)	−0.021**	(0.009)	−0.021**	(0.009)
HAL-Sued · trend	−0.024*	(0.013)	−0.024*	(0.013)	−0.022*	(0.012)
Harz · trend	0.011	(0.011)	0.011	(0.012)	0.012	(0.011)
MD-HAL · trend	−0.022***	(0.007)	−0.022***	(0.007)	−0.022***	(0.007)
MD-Nord · trend	0.008	(0.014)	0.008	(0.014)	0.007	(0.013)
MD-Ost · trend	−0.022*	(0.013)	−0.022*	(0.013)	−0.021	(0.013)
ST-Sued · trend	−0.016	(0.012)	−0.016	(0.012)	−0.013	(0.012)
Vorharz · trend	−0.006	(0.012)	−0.006	(0.012)	−0.005	(0.012)
Location classes	yes		yes		yes	
Observations	10,778		10,778		10,778	
$Cor_{P,\hat{P}}$	0.676		0.676		0.677	
Residual Std. Error	0.326 (df = 10,739)		0.326 (df = 10,738)		0.325 (df = 10,736)	

Note: Clustered standard errors (at thirty quantiles of lot size and the squared soil quality) in parentheses.
Asterisks indicate the following: * = p<0.1; ** = p<0.05; *** = p<0.01.

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